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Why are open ascending auctions popular? The role of information aggregation and behavioral biases

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The popularity of open ascending auctions is often attributed to the fact that openly observable bidding allows to aggregate dispersed information. Another reason behind the frequent utilization of open auction formats may be that they activate revenue enhancing biases. In an experiment, we compare three auctions that differ in how much information is revealed and in the potential activation of behavioral biases: (i) the ascending Vickrey auction, a closed format; and two open formats, (ii) the Japanese–English auction, and (iii) the Oral Outcry auction. Even though bidders react to information conveyed in others' bids, information aggregation fails in both open formats. In contrast, the Oral Outcry raises higher revenue than the other two formats by stimulating bidders to submit unprofitable jump bids and triggering a quasi-endowment effect.

Keywords. Ascending auctions, information aggregation, jump bidding, auction fever.

JEL classification. C90, D44, D82.

1. Introduction

Open ascending auctions are routinely preferred to sealed-bid formats by both private platforms (e.g., Amazon, eBay, Catawiki) and policy makers, for example, in the allocation of spectrum rights (McMillan (1994), Milgrom (1989, 2004)). One compelling theoretical reason for their popularity is that open ascending auctions allow bidders to endogenously aggregate dispersed information due to the observability of the bids. Stan-

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dard theory predicts information aggregation to have two advantages: it allows for a more precise estimate of the value and it leads to higher revenues in expectations. In single-unit auctions with affiliated values, buyers who are better informed bid more aggressively (Milgrom and Weber (1982)). This is implied by the linkage principle, according to which average revenues are increased by providing bidders with more information about the value of the item for sale. To this date, the linkage principle remains highly influential and is often cited as the reason why open auctions are and should be preferred over sealed-bid formats.[1]

Empirically, however, it remains an open question whether open ascending auctions are indeed capable of aggregating information. One challenge is that the single-unit setup with affiliated values hosts multiple equilibria (Bikhchandani, Haile, and Riley (2002)). This multiplicity may impede information aggregation (Milgrom (2004, p. 197)). Another challenge is that some open ascending auctions allow for jump bidding, which may obfuscate information (Avery (1998), Ettinger and Michelucci (2016)). Also, in every-day auctions, particularly those involving non-professional bidders, the reasoning required to infer information from the bidding of others may be too demanding.

Aside from their potential for information aggregation, open ascending auctions may also differ from closed formats in the extent to which they activate or mitigate behavioral biases. Some of these biases provide alternative mechanisms for raising revenues. For instance, it is common for open ascending auctions to provisionally award the item during the auction to the bidder who submits the highest standing bid. As a result, auction fever may be activated, which encourages overbidding and leads to a quasi-endowment effect (Heyman, Orhun, and Ariely (2004), Ehrhart, Ott, and Abele (2015)). Another possibility is that open ascending auctions encourage naïve jump bidding, for instance, when bidders are impatient and want to terminate the auction quickly. In contrast to when jump bidding is motivated by strategic reasons, naïve jump bidding may easily enhance revenues.[2] Open ascending auctions may also encourage spiteful bidding because bidders can condition their overbidding on the presence of other remaining active bidders (Andreoni, Che, and Kim (2007), Bartling, Gesche, and Netzer (2017)). There is, however, also a possibility that open ascending auctions mitigate behavioral

[1]In a policy report on the question whether the spectrum auctions ran in the UK in 2018 should use an open or sealed-bid design, PowerAuctions (2015, p. 6) writes: "... an auction should be structured in an open fashion that maximizes the information made available to each participant at the time she places her bids (Paul R. Milgrom and Robert J. Weber (1982a)). When there is a common value component to valuation and when bidders' signals are affiliated, an open ascending-bid format may induce participants to bid more aggressively (on average) than in a sealed-bid format, since participants can infer greater information about their opponents' signals at the time they place their final bids." In a footnote, they explain that the text is quoted from Ausubel (2004), and add that "Its assessment is typical of the consensus of the auction literature today." The NERA (2017) report also favors an open ascending auction and echoes the same view on page 11: "Auction theory tells us that price discovery can ease common-value uncertainty, and encourage bidders to bid a higher proportion of value ... "

[2]Probably the most preposterous auction ever was decided by a naïve jump bid. After murdering the Roman emperor Pertinax (A.D. 193), the praetorian guard offered the Roman empire for sale in an ascending auction. Julianus topped Sulpicianus' highest bid of 20,000 sesterces per soldier by a winning bid of 25,000 sesterces. The winning bid corresponded to 5 years of wages of each of the 10,000 praetorians. After Julianus defaulted on his bid, he was murdered after a reign of only 66 days (Klemperer and Temin (2001)).

biases. For example, the higher transparency of open formats may lead to buyers becoming aware of the winner's curse and tame the overbidding (Levin, Kagel, and Richard (1996)). When the winner's curse is mitigated, lower revenue may be the result in an open ascending auction.

In this paper, we explore whether open auctions do raise higher revenues than sealed-bids formats. Moreover, we disentangle whether this is due to information being successfully aggregated or other behavioral mechanisms.

eBay provides a natural setting to explore information aggregation and revenues in open auctions. eBay uses an open ascending format, which allows for jump bidding and provisionally awards the good to the highest standing bidder. Thus, both information aggregation and revenue-enhancing biases are possible in this format. We collected eBay data for one of the most frequently auctioned cell phones at the time of the study. The field-data analysis that we report in the Appendix, Section A.1, offers suggestive evidence that information endogenously generated during the auction (proxied by the price reached halfway through the auction) and jump bidding (proxied by the average increment per bidder) correlate positively with final prices. On the basis of a median split, we find that above median bidding in the first-half of the auction corresponds to an increase of 67% in the final price. Likewise, with a median split on the average increment per bidder, we find above median increments between consecutive bids correspond to an increase of 14% of the final price. The findings are consistent with information aggregation and also with the presence of revenue-enhancing naïve jump bidding. However, such data has severe limitations. First, the direction of causality is unclear. Second, such data is lacking crucial insights about bidders' information and the value of the item for sale, which makes it impossible to separate behavioral mechanisms from information aggregation. Third, we miss data from an appropriate control condition, that is, a counterfactual auction, which does not allow for information aggregation.

To overcome these limitations, we employ a laboratory experiment where we randomly assign subjects to three different auction formats. These differ in the information revealed during the bidding process, and possibly also in the extent to which different behavioral biases can be triggered. To ensure comparability, all formats use a second-price rule.

The first auction format is the Japanese–English auction, an open ascending auction with irrevocable exits. In this format, a clock tracks the ascending price and bidders withdraw from the auction until a single bidder remains, who wins the auction and pays the last exit price. The exit prices of other buyers are publicly observed. These bids then allow to infer other bidders' private signals, which are informative about the common value.

The second auction format is the ascending Vickrey auction, a sealed-bid ascending auction. It is implemented identically to the Japanese–English auction with an ascending clock and irrevocable exits. However, exits are not observable by others, thereby eliminating the possibility of information aggregation.

The third format we run is the Oral Outcry auction, modeled to fit popular auction designs. It falls between the other two in terms of its potential for information aggregation. In this auction, bidders can control how much information is revealed. They can engage in the informative, incremental bidding that characterizes the Japanese–English auction. They can also engage in jump bidding, that is, outbid the standing bid by a nonnegligible amount. Jump bidding can be used rationally, for instance, to obfuscate information (Ettinger and Michelucci (2016)) or to signal to other bidders that it is better to back off (Avery (1998)). Jump bidding could also be used naïvely by impatient bidders. The Oral Outcry auction, while still allowing for information aggregation, may also be the most conducive to revenue-enhancing biases. This is the only format that allows bidders to submit naïve jump bids, and it is also the only format that can activate auction fever by provisionally awarding the good during the auction.

The comparison between the ascending Vickrey auction and the Japanese–English auction provides a clean comparison of the role of information aggregation, since these formats differ only in the public revelation of exits. Theoretically, rational bidders use the information revealed in the auction to form a more precise estimate of the common value, which makes them less fearful of the winner's curse (Milgrom and Weber (1982)). As a result, the Japanese–English auction is expected to raise higher revenue than the ascending Vickrey auction. Remarkably, this prediction is reversed if bidders are naïve and tend to fall prey to the winner's curse. By gradually revealing the exit prices of bidders with low signals, the Japanese–English auction could make the risk of suffering from the winner's curse more transparent, thus taming the overbidding and reducing revenues compared to the ascending Vickrey auction. This intuition is captured by signal averaging models, which we describe more precisely in Section 3.

When information is successfully aggregated, remaining bidders' uncertainty about the common value is reduced and prices approximate the underlying common value more closely (Wilson (1977), Kremer (2002)). We evaluate information aggregation by comparing the squared distance between the price and the common value across formats.

We further decompose information aggregation into two components: (i) the extent to which bids are objectively informative of the common value (*information revelation*); and (ii) the extent to which bidders actually use this information effectively in their own bidding (*information processing*).

We find that in the Japanese–English auction, less information than expected is generated. One factor that contributes to this finding is that some bidders with a low signal display spiteful behavior and stay in the auction longer than they would in the ascending Vickrey auction. Such heterogeneity is not observable by the remaining bidders and degrades the quality of the revealed information. In addition, bidders are processing the available information suboptimally. Even though bidders are responding appropriately to the fact that early bids are revealing little information by largely disregarding them, the potential to aggregate the information actually available is mostly not realized. Instead, the processing of information is qualitatively in agreement with signal averaging heuristics. This combination of noisy early bids and suboptimal information processing leads to a failure of information aggregation. Although subjects have only access to their private information in the ascending Vickrey auction, more information is aggregated: the squared distance between prices and common value is lower in the ascending Vickrey than in the Japanese–English auction, in which additional information is available.

Surprisingly, bids in the Oral Outcry and Japanese–English auction reveal a similar amount of information about the common value. That is, bidders do not make extensive use of the potential to strategically hide their information via jump bidding. However, in the Oral Outcry auction, the available information is processed to an even smaller extent than in the Japanese–English auction. Here, final bids are substantially distorted by the quasi-endowment effect and rash jump bidding. Subjects who are prone to endowment effects on a questionnaire measure tend to stay too long in the auction and earn substantially lower payoffs. Additionally, this auction encourages many bidders to submit unfounded jump bids. These forces result in systematic overbidding and a price which is the poorest predictor of the common value across our auction formats.

The interplay of all aforementioned factors leads to similar revenues in the Japanese–English auction and the ascending Vickrey auction. Highest revenues are observed in the Oral Outcry auction. The rationale for why the Oral Outcry auction is most often observed in the field may be quite different from the understanding in the theoretical and policy-oriented literature. Instead of leading to information aggregation, it triggers behavioral biases such as the quasi-endowment effect and reckless jump bidding.

In many ways, the laboratory provides the ideal environment to study how information is generated and processed. An important question is whether experimental results generalize to the field. Our experiments use nonprofessional bidders (students) that bid for objects with moderate values (of approximately €25). We think that this situation is representative for most online auctions in the field. Beyond everyday auctions involving consumers, some of our results may also extrapolate to some situations involving professional bidders. For instance, Dyer, Kagel, and Levin (1989) find that professional bidders in the construction industry fall prey to the winner's curse in the same way as students do. We do not claim that our results generalize to spectrum auctions where bidders seek the advice of game theorists.[3]

The remainder of the paper is organized in the following way. Section 2 reviews the literature, Section 3 presents the game and some theoretical benchmarks, Section 4 describes how information aggregation is evaluated. Section 5 presents the experimental design and procedures. Section 6 discusses the experimental results and Section 7 concludes. The Online Supplementary Material (Offerman, Romagnoli, and Ziegler (2022)) presents additional analyses in Appendix A, the instructions in Appendix B, and it includes the data and the code for empirical analyses.

2. Related literature

Previous laboratory studies have documented how people succumb to the winner's curse in common value auctions. For an overview, see Kagel and Levin (2014). Eyster and Rabin (2005) and Crawford and Iriberri (2007) present behavioral models to explain the

[3]Nevertheless, it is interesting to note that also in those auctions bidders sometimes engage in bidding that is merely motivated to drive up the price for a competitor. Such bidding may be driven by a spiteful motivation, or by a predatory desire to weaken the competitor in a future market (Levin and Skrzypacz (2016)). When bidding behavior may be driven by such considerations, it becomes very hard to infer valuable information from competitors' bids.

winner's curse. Recent studies have studied pathways behind the winner's curse, highlighting that problems with contingent reasoning (Charness and Levin (2009)) and disentangling the importance of belief formation and non-optimal best responses (Charness and Levin (2009), Ivanov, Levin, and Niederle (2010), Camerer, Nunnari, and Palfrey (2016), Koch and Penczynski (2018)). We compare whether open auctions mitigate or worsen the importance of behavioral biases such as the winner's curse. Levin, Peck, and Ivanov (2016) find that a Dutch auction lessens a winner's curse compared to sealed bid formats.

An important strand of literature investigates whether markets are capable of aggregating dispersed information. A series of experiments have investigated information aggregation in asset markets. Results have been mixed. Plott and Sunder (1988) find that information aggregation only occurs when preferences are homogeneous or when a complete set of contingent claims can be traded. Forsythe and Lundholm (1990) find that information aggregation only succeeds with trading experience and common knowledge of dividends. Hence, information aggregation seems to fail when the inference task is complicated by the presence of several dimensions of uncertainty, or when the information conveyed by prices in equilibrium is less naturally interpretable.

How information is processed is also studied in the context of auctions, a particularly important form of a market. Several papers study the effect of an auctioneer exogenously revealing information in auctions. Kagel and Levin (1986) and Kagel, Levin, and Harstad (1995) show that there are ambiguous effects of revealing information in first-price and second-price sealed-bid auctions. In a setting with both private and common value elements, Goeree and Offerman (2002) find that high-quality reports of the auctioneer can positively affect efficiency and revenue, but to a lower extent than predicted by theory.[4] In contrast to this work, our paper explores *endogenous* information aggregation. Aside from shedding light on revenue effects, we uncover the process of how bidding generates information in auctions, and how bidders process the available information.

Close to our work, Levin, Kagel, and Richard (1996) compare the performance of the Japanese–English auction and the first-price auction in a common value setting. They find that the revenue comparison of the Japanese–English auction and the first-price auction depends on the experience of the bidders: with inexperienced bidders the first-price auction raises more revenue. However, with experience this effect disappears and is sometimes reversed. Changing the price-rule and the auction format across treatments simultaneously complicates identifying the effect that information aggregation has on the outcomes. As a result, their paper remains silent about the extent to which the endogenous information revealed in the Japanese–English auction allows bidders to actually aggregate information. On an individual bidder level, they cannot use the sealed-bid auction as a benchmark to measure the degree of information processing in the Japanese–English auction. Their focus is more on a revenue comparison of their two auction formats, instead of evaluating the extent to which information is aggregated empirically. Shedding light on this phenomenon is a key contribution of our paper. We also

[4] Dufwenberg and Gneezy (2002) study another form of exogenous information disclosure. They find that the disclosure of losing bids after first-price sealed-bid common value auctions reduces revenue.

contribute by showing that bidders process revealed information, as our design allows to compare Japanese–English and second-price sealed-bid auctions that only differ in the observability of information. Levin, Kagel, and Richard (1996) only provide evidence that bids correlate with previous dropouts in their Japanese–English auction, which may be driven by mechanical correlation introduced by arranging bids into order statistics (as we explain in Section 6.2). They do not, and due to the differences in pricing rules cannot, provide evidence that bids do respond to revealed dropouts. Another important difference is that their analysis does not include the Oral Outcry auction, which triggers the revenue enhancing biases that may explain their actual popularity. A less important difference is that Levin, Kagel, and Richard (1996) adopt uniformly distributed values and signals, a knife-edge case where in equilibrium rational bidders will only process the lowest dropout price and disregard all other exit decisions in the Japanese–English auction.

A related literature compares different auction formats when bidders have interdependent valuations. In such environments, the linkage principle does not hold; with symmetric bidders, expected revenue and efficiency are predicted to be the same across auction formats (Goeree and Offerman (2003a)). Some experimental papers introduce specific asymmetries that break the revenue and efficiency equivalence results. For instance, Kirchkamp and Moldovanu (2004) compare efficiency between the Japanese–English and second-price sealed-bid auctions in a particular setup with interdependent values, where a bidder's value is the sum of the own private signal and one specific signal of the other bidders. In that setup, they find that the Japanese–English auction generates higher efficiency.

Boone, Chen, Goeree, and Polydoro (2009) and Choi, Guerra, and Kim (2019) compare open and sealed-bid auctions with interdependent values in the presence of insiders, to whom the value of the item for sale is revealed. In line with their theoretical predictions, revenue and efficiency increases in the Japanese–English auctions.[5]

In contrast to this work, our paper sheds light on how bidders process information in the more common case where signals are affiliated. We investigate the case in which the linkage principle applies and information revelation occurs with symmetric bidders. As Perry and Reny (1999) note, "The linkage principle has come to be considered one of the fundamental lessons provided by auction theory." Another distinction between our approach and this literature is that we study how information is aggregated directly, instead of by relying on comparative statics effects, which are predicted by information aggregation. We do so by employing measures of information aggregation frequently used to theoretically evaluate information aggregation in auctions; see, for example, Wilson

[5]A different kind of interdependence is studied in the multiunit auction experiments of Betz, Greiner, Schweitzer, and Seifert (2017). They consider the sale of multiunit private values emission certificates of this year (good A) and of next year (good B). Interdependence is created because units of type A can be used as type B unit, but not vice versa. Their treatment variables are the type of auction and whether goods are auctioned sequentially or simultaneously. When items are auctioned simultaneously, they find that open ascending auctions are more efficient than sealed-bid auctions. Auctioning the items sequentially enhances the performance of sealed-bid auctions but leaves the efficiency of ascending auctions unaffected. In each auction format, total revenues are higher when items are sold sequentially.

(1977), Pesendorfer and Swinkels (2000) and Kremer (2002). Our results show that although revenue is increased in some of our formats, this occurs while information aggregation *decreases*, opposite to the theoretical prediction.

We also contribute to the literature on the Oral Outcry auction. Roth and Ockenfels (2002) study the impact of different rules for ending internet auctions at eBay and Amazon on bidders' propensity for late bidding. Amazon's rule to extend bidding deadlines if new bids are submitted resembles our procedure. In the lab, Ariely, Ockenfels, and Roth (2005) find that Amazon's rule to extend bidding deadlines generates higher revenue than eBay's in a private value setting. Cho, Paarsch, and Rust (2014) provide field evidence and show that in the comparison of two open auction formats, an open outcry English auction format raises more revenue, which they attribute to endogenous information revelation. It can however not be excluded that the higher revenue in the open outcry auction is actually due to behavioral factors. Close to our experiment, Gonçalves and Hey (2011) compare a Japanese–English and an Oral Outcry auction and find that they result in approximately equal revenue. However, they focus on auctions with only two bidders, which means that the potential of the Japanese–English auction to generate endogenous information is excluded by design.

It is also instructive to contrast what can be learned from our work compared to a structural approach that uses field data. For instance, Haile and Tamer (2003) use data from Oral Outcry auctions of timber-harvesting contracts held by the U.S. Forest Service to infer information about bidders' valuations. In a private values model, they show what can be learned from two simple assumptions (i) bidders do not bid above value, and (ii) bidders do not drop out unless the price is higher than their value. Their approach allows the researchers to find bounds on the valuations of bidders. Such information is useful, for instance to investigate whether reserve prices are set optimally. In contrast, in our laboratory experiment, we observe the common value and the signals. This allows us to investigate how information is revealed, processed, and aggregated in strategically more complicated common value auctions, and how this depends on the auction format. More importantly, where the structural approach takes rationality as a given, our approach makes it possible to identify potential behavioral biases. In fact, we find that behavioral biases are key to explain the popularity of Oral Outcry auctions in comparison to other second-price formats.

Finally, we relate to the literature on endogenous information processing in stylized games. Anderson and Holt (1997) initiated a literature on informational cascades. Eyster, Rabin, and Weizsacker (2018) find that subjects' social learning depends on the complexity of the underlying problem. Magnani and Oprea (2017) investigate why subjects violate no-trade theorems and find that overweighting of one's private information contributes to such violations. Hossain and Okui (2018) study how subject's correlation neglect (Enke and Zimmermann (2019)) explains information processing. Other studies show that biased inference can arise in in-transparent problems where subjects display a lack of contingent reasoning (Esponda and Vespa (2014), Ngangoué and Weizsäcker (2021), Martínez-Marquina, Niederle, and Vespa (2019)). Our take-away from this literature is that subjects do pay attention to the behavior of others, but that their sophistication depends on specifics of the problem, such as the transparency of its presentation and its complexity. There is no single result that generalizes across all contexts. In our view, this implies that social learning should be studied in the particular setup of interest. How information is processed and aggregated in the canonical affiliated values setup of Milgrom and Weber (1982) is therefore still an open question. While this setup not only inspired a vast body of theoretical work, it also was and continues to be very influential in advice on actual auction design (McMillan (1994, pp. 151–152) and Cramton (1998)).

3. Auction formats and theoretical benchmarks

In the following, we describe the auctions implemented in the laboratory, present Nash equilibria as well as behavioral heuristics, and explain revenue predictions.

3.1 *General setup: Bidders and payoffs*

All our formats are common value auctions with five bidders and a second-price rule. The common value of the object for sale is unknown to bidders, who only receive a private signal about the value. More precisely, the good has value V, where $V \sim \mathcal{N}(\mu, \sigma_V) = \mathcal{N}(100, 25)$. Each bidder $i \in \{1, 2, \dots, 5\}$ receives a signal X_i of the common value V. This signal is the sum of the underlying value and an individual error ϵ_i:

$$X_i = V + \epsilon_i.$$

This error is *i.i.d.* across bidders and normally distributed with mean 0 and standard deviation σ_ϵ: $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon) = \mathcal{N}(0, 35)$.

In all formats, the winner of the auction is the bidder who submits the highest bid. This bidder receives a payoff equal to V minus the second highest bid. All the other bidders receive a payoff of 0. For notational purposes, define a signal realization x_i for bidder i. Let $Y_{i,(k)}$ represent the kth highest of the signals received by any other bidder $j \neq i$. So, for example, $Y_{i,(1)}$ is the highest signal received by any bidder other than bidder i.

3.2 *Auction formats*

We now provide details for each of the three auction formats we study.

The ascending Vickrey auction (AV) We implement the ascending Vickrey auction (AV) with a clock procedure. After bidders have been privately informed of their signals, the price rises simultaneously from 0 for all participants. At any integer price 0, 1, 2, 3, ..., bidders can decide to leave the auction by pressing the “EXIT”-button. In the AV, no bidder observes whether any other bidder has left. The auction stops as soon as four bidders have exited the auction. The last remaining bidder wins the auction and pays the price at which the fourth bidder leaves. In case multiple bidders leave last at the same price, one of them is randomly selected to be the winner and pays the price at which she left. In this format, a bid is the price at which the bidder decided to leave the auction.

The Japanese–English auction The Japanese–English auctions (JEA) makes use of the same clock procedure. Differently from the AV, all remaining bidders are notified in real time of other bidders' exit prices. Like in the AV, the winning bidder is the last remaining bidder after four bidders exit. This bidder pays the price at which the fourth bidder left the auction.

The Oral Outcry auction In the Oral Outcry auction (OO), bidders can outbid each other repeatedly and by arbitrary amounts until no more out-bidding takes place and the good is awarded to the highest standing bidder. In our implementation, bidding proceeds in bidding rounds. In each bidding round, all bidders have 15 seconds to submit a maximum bid. As soon as one bid is submitted, the bidding round is interrupted. At this point, the bidder who submitted the highest bid becomes the standing bidder, the provisional winner in case the auction would stop afterwards. The current price is set to the second highest bid at this moment. A new bidding round starts, the clock is reset to 15 seconds and the standing bidder is excluded from submitting a new bid.[6] During the auction, bidders are notified of the highest maximum bid of each of the other bidders, with the exception of the current standing bidder, about whom it is only revealed that her highest bid is at least as high as the current price. The auction ends as soon as the countdown elapses without further bidding. At this point, the last standing bidder wins the auction. She pays the last current price, which is the second highest bid at the end of the auction.

3.3 *Nash equilibrium predictions and behavioral forces*

In this section, we use game theoretic results, behavioral theories, and recent experimental findings to contextualize our research questions. We start with presenting the Nash equilibrium predictions, according to which the JEA should aggregate information, and consequently lead to higher revenues than the AV.

AV and JEA: Nash equilibria and the linkage principle Symmetric Nash equilibria in single-unit auctions with affiliated values have been derived in Milgrom and Weber (1982). In the AV, a bidder's strategy can be described by a reservation price, which makes this format strategically equivalent to the standard second-price sealed-bid auction (see Milgrom (2004, pp. 187–188)). A symmetric equilibrium of the AV is given by bids $b(x_i)$:

$$b(x_i) = \mathbb{E}[V|X_i = x_i, Y_{i,(1)} = x_i].$$

That is, each bidder exits the auction as soon as the clock reaches the expected value of the good for sale conditional on her signal and assuming that the highest signal obtained by other bidders is also x_i.[7]

[6] This leads to an auction ending time being determined endogenously. Such a rule is a feature of online auctions at amazon.com, yahoo.com, and catawiki.com.

[7] In our experimental setup with 5 bidders and normally distributed values and signals, Goeree and Offerman (2003b) show that the above conditional expectation is equal to $b(x_i) = \mathbb{E}[V|X_i = x_i, Y_{i,(1)} = x_i] = x_i - \frac{\int_{-\infty}^{\infty} \epsilon \phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}{\int_{-\infty}^{\infty} \phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}$, where $\phi_V(\cdot)$ denotes the pdf of the common value distribution, $\phi_\epsilon(\cdot)$ the pdf of the error distribution, with its cdf $\Phi_\epsilon(\cdot)$.

In the symmetric Nash equilibrium of JEA, bidders include endogenously revealed information into their bidding strategies. The first bid is given by (see Milgrom and Weber (1982))

$$b_1(x_i) = \mathbb{E}[V | X_i = x_i, Y_{i,(1)} = x_i, \dots, Y_{i,(4)} = x_i].$$

Just like in the AV, the first exit bid is obtained via a conditional expectation, assuming that all other bidders hold an equally high signal. However, as soon as the first bidder drops out at p_1, the remaining bidders perfectly infer the signal of the exiting bidder, from $p_1 = b_1(Y_{i,(4)})$. All bidders dropping out subsequently base their jth bid (for $j > 1$) on their private information and the signals inferred from the $j-1$ observed dropouts. The remaining bidders bid $b_j(x_i)$:

$$\begin{aligned} b_j(x_i) = \mathbb{E}\big[V | X_i = x_i, Y_{i,(1)} = x_i, \dots, Y_{i,(5-j)} = x_i, p_1 = b_1(Y_{i,(4)}), \dots, \\ p_{j-1} = b_{j-1}(Y_{i,(5-j+1)})\big]. \end{aligned}$$

This equilibrium allows to iteratively back out all information except the one contained in the highest signal.[8] According to the *linkage principle*, the information revealed in the JEA leads to more aggressive bidding, the fourth bid in the JEA is on average higher than the fourth bid in the AV (Milgrom and Weber (1982)). Bikhchandani, Haile, and Riley (2002) have identified other symmetric Nash equilibria that implement the same outcome. In such equilibria, the first three bidders drop out at a fraction $\alpha \in (0, 1)$ of the bids at which they dropped out in the just described equilibrium, and the last two bidders bid as before.[9]

AV and JEA: A behavioral perspective Overbidding is often observed in experimental common value auctions, suggesting that in practice bids may not align well with Nash equilibrium predictions. Even in the AV, bidding in agreement with a symmetric equilibrium is quite sophisticated and requires bidders to (i) use their prior about the distribution of the value; (ii) account for the fact that the bidder with the highest signal is predicted to win the auction. Thus, to avoid the winner's curse, bids need to be shaded.

Simpler behavioral rules have been proposed in alternative to Nash equilibrium bidding. For example, bidders in the AV who ignore both (i) and (ii), and only rely on their private signal, may adopt the "bid signal"-heuristic (Goeree and Offerman (2003b)): $b(x_i) = x_i$, which leads to expected overbidding.

[8]We determine Nash equilibrium bids in our setup, using a result by DeGroot (2005, p. 167). For inferred or assumed signal realizations by bidder i, define $\bar{x}_i = \frac{1}{5}(\sum_{j=1}^{4} Y_{i,(j)} + x_i)$. Then in equilibrium each bidder i bids: $\mathbb{E}[V | x_i, Y_{i,(1)} \dots, Y_{i,(4)}] = \frac{\frac{\mu}{\sigma_V^2} + \frac{5\bar{x}_i}{\sigma_\epsilon^2}}{\frac{1}{\sigma_V^2} + \frac{5}{\sigma_\epsilon^2}} = \frac{5\bar{x}_i \sigma_V^2 + \mu \sigma_\epsilon^2}{5\sigma_V^2 + \sigma_\epsilon^2}$. On request, we provide derivations showing that equilibrium bids can be inverted such that they depend linearly on the signal and observed bids. This also applies to all other models considered in this paper. We therefore restrict ourselves to linear information use in all estimations.

[9]Bikhchandani and Riley (1991) study asymmetric Nash equilibria and show that they can lead to different revenue rankings than those established by Milgrom and Weber (1982). In our experiment, all bidders are treated symmetrically and there is nothing that facilitates coordination on an asymmetric equilibrium. In this sense, a symmetric equilibrium is more plausible.

The JEA, on the other hand, allows bidders to observe early exits of other bidders with low signals. This could make (ii), i.e., the fact that winning bidders receive higher signals than their peers, transparent to bidders in a natural way. The "bid signal"-heuristic remains available in the JEA. However, by raising awareness about the winner's curse, the JEA can lead to less overbidding. The "signal averaging rule" proposed by Levin, Kagel, and Richard (1996) captures this intuition. According to this rule, bidders bid an equally weighted average of their own signal and the signals of their fellow bidders, revealed from the previous dropouts. After $j-1$ bidders dropped out, with the vector of revealed signals being $\mathbf{Y}_i = \{Y_{i,(4)}, \dots, Y_{i,(5-j+1)}\}$, this implies the following bid: $b_j(x_i, \mathbf{Y}_i) = \frac{1}{j}x_i + \frac{1}{j}\sum_{k=1}^{j-1} Y_{i,(5-k)}$.[10] In expectation, the "signal averaging rule" corrects for the overbidding observed in the "bid signal"-heuristic. If bidders follow these two behavioral rules in the JEA and the AV, respectively, then the former format is predicted to raise lower revenues.

Somewhat more sophisticated bidders could process information about the prior distribution of the value, and thereby accommodate (i), incorporating information on the prior. This would lead to a slightly modified versions of the two rules above, the "Bayesian bid signal"-heuristic, and the "Bayesian signal averaging rule." By anchoring bidding to the prior, these rules lead to less extreme under and overbidding; however, they continue to predict that the JEA raises lower revenues than the AV.

In the "Bayesian bid signal"-heuristic bidders bid the expected value of the good for sale, conditional on one's signal: $b(x_i) = \mathbb{E}[V|x_i] = x_i - \mathbb{E}[\epsilon_i|x_i]$. Goeree and Offerman (2003b) show that $b(x_i) = \frac{\sigma_V^2 x_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$. According to the "Bayesian signal averaging rule," bidders combine Bayes rule with the symmetric signal averaging rule.[11] After $j-1 > 0$ observed dropouts, bidder i calculates the average of available signals $\bar{x}_i = \frac{1}{j}x_i + \frac{1}{j}\sum_{k=1}^{j-1} Y_{i,(5-k)}$ and bids $b(\bar{x}_i) = \frac{\sigma_V^2 \bar{x}_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$.

Nash equilibrium predictions and predictions based on behavioral rules now lead to conflicting effects of information revelation on revenues. While private signals can be inferred in both types of benchmarks, revenue ranking predictions with the behavioral rules are driven by the degree to which bidders' are made aware of the winners' curse in the JEA relative to the AV.

Using our parameterization and draws, Table 1 summarizes the revenue predictions for the Nash equilibrium and the behavioral models that we discussed.[12]

Nash equilibrium revenues are only slightly higher in the JEA than in the AV. This is not an artifact of our parameter choices. As we show in Appendix Section A.2, similar

[10] Note that this rule can be plugged in iteratively, such that bidding depends only on the most recent dropout, which is an average of all previously revealed signals. This yields $b_j(x_i, b_{j-1}) = \frac{1}{j}x_i + \frac{j-1}{j}b_{j-1}$.

[11] A peculiar feature of the setup of Levin, Kagel, and Richard (1996) with uniformly distributed values and signals is that a Bayesian will form the same belief as a naïve bidder who ignores the prior. This is not the case in our setup with normally distributed values and errors.

[12] Note that the revenue prediction of a model only depend on the revenue-determining bidder using the particular model. Theoretically, in the JEA, bidders are able to infer all other bidders' signals irrespective of the model that these other bidders are using, as long as all bidders hold correct beliefs on which model others are using.

Table 1. Revenue predictions.

	AV	JEA
Nash equilibrium	95.8	97.4
Bid signal	117.4	117.4
Signal averaging rule	117.4	91.1
Bayesian bid signal	105.9	105.9
Bayesian signal averaging	105.9	94.0

minor revenue differences result for various combinations of variances of the values and errors. In both formats, the winners capture some information rents and make positive profits, as the price-determining bidder in equilibrium slightly underestimates the value by design of the equilibrium bidding strategies.

The differences in predictions for the behavioral models are much larger. Moreover, the behavioral rules yield losses for the winners in the AV. In the JEA, bidders make substantial profits if they use (Bayesian) signal averaging rules.[13]

The Oral Outcry: Information aggregation and behavioral biases The Oral Outcry auction format is very rich and there are no clear Nash equilibria for this format. Still, we can make some observations about the potential of the Oral Outcry for information aggregation and revenues. In this format, bidding may proceed incrementally as in the Japanese–English auction. That is, bidders may constantly be active until their reservation price is reached, which would allow for similar inference as in the JEA.

This format can also encourage jump bidding. From a strategic point of view, jump bidding can be used to signal a high estimated value of the item and deter other bidders from continuing to bid. Avery (1998) shows how strategic jump bidding can be supported in an equilibrium of a game that is much simpler than ours. Similarly, jump bidding may obfuscate information, as shown in a stylized auction game in Ettinger and Michelucci (2016). In either case, severe jump bidding suppresses information aggregation and its revenue-enhancing effects.

On the other hand, recent experimental findings suggest that some features in Oral Outcry may be particularly prone to revenue-enhancing behavioral biases, such as auction fever (Heyman, Orhun, and Ariely (2004), Ehrhart, Ott, and Abele (2015)). Similarly, jump bidding might not be used in the sophisticated way studied theoretically, for example, it might rather be driven by bidders' impatience.

4. Information aggregation: Measure and benchmarks

When information is successfully aggregated, bidding and prices move closer to the underlying common value (Wilson (1977), Kremer (2002)). We measure the degree of information aggregation with the squared distance between the price and the common value

[13]Note that our experimental setup leads to low expected revenue with signal averaging-rules. This allows us to test the rules beyond what was possible in Levin, Kagel, and Richard (1996). In their setup, signal averaging-rules lead to predictions more similar to Nash equilibrium revenues.

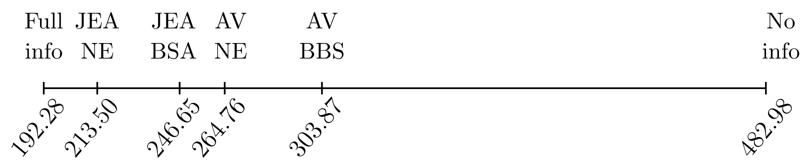

FIGURE 1. Squared distance to common value—JEA and AV.

and compare it across formats (Hanson, Oprea, and Porter (2006)). A distance of 0 would imply perfect information aggregation in the sense that bidders inferred the exact true value. Figure 1 displays the relevant measures for the setup of our experiment.

The possibility of perfect inference is curtailed by the noisiness of the signals. We account for the maximal information potentially available, the one contained in the five signals, by computing the Full Information benchmark. In it, all five signals are revealed and bidders bid the conditional expected value of the item given these signals. Additionally, we model the lowest degree of aggregation with the No Information benchmark, where bidders bid the prior average common value, thus ignoring also their own private signal.

We illustrate the Full and No Information benchmark as the lower and upper bounds of a segment measuring information aggregation. On this segment, lower values indicate a better approximation of the common value by the price, hence improved information aggregation.

In the segment, we also show how much information aggregation is predicted in Nash equilibrium and by some exemplary behavioral models. In the Nash equilibrium of the JEA, we see that the Full Information benchmark is almost attained.[14] In the Nash equilibrium of the AV, the squared distance to the common value is higher, as less information aggregation is possible. By comparing the Nash equilibrium predictions of the two formats, we see the theoretical impact of information aggregation: If dropouts are observable, bidders obtain a more precise estimate of the value and the price follows the common value more accurately.

The prediction that the JEA leads to higher information aggregation compared to the AV generalizes to the behavioral models of bidding behavior. The Bayesian bid signal heuristic (BBS) in the AV auctions predicts a larger dispersion around the common value compared to Bayesian signal averaging (BSA) in the JEA.[15] Therefore, even when processing information in a suboptimal manner, bidders are predicted to improve their estimate of the value when they observe others' bids.

5. Experimental design and procedures

The computerized laboratory experiment was conducted in July and October 2018 at the CREED laboratory of the University of Amsterdam. In total, we ran 30 sessions with

[14] It is not fully attained for two reasons: (i) the bid determining the price is based on 4, rather than 5, signals; (ii) bidders maximize expected profit, with information rents for the winner.

[15] This also holds for the comparison of signal averaging- and bid signal-heuristics, which are omitted for brevity.

10 subjects each. We preregistered this experiment (Offerman, Romagnoli, and Ziegler (2019)). Most subjects were students of business, economics, or other social sciences, with 50.7% being male and an average age of 23. Each subject participated in only one session.

The experiment was conducted in a laboratory with soundproof cubicles. As a consequence, information revelation was entirely controlled as intended in the experimental design. In Appendix B, we present the instructions together with screenshots of the auction interface for all formats. Subjects read the computerized instructions at their own pace, and they had to correctly complete a set of test questions before they could proceed to the experiment. Before the experiment started, subjects received a handout with a summary of the instructions. At the end of the experiment, subjects filled out a brief questionnaire.

In the experiment, 30 auction rounds were played. Payment was based on five rounds randomly selected at the end of the experiment. Subjects earned points that were exchanged according to a rate of € 0.25 for each point. Subjects earned on average € 24.28 (standard deviation: 6.02, minimum earnings were set to € 7) in approximately 2 hours.[16]

We run three between-subject treatments, each corresponding to one auction format. In each ten-subject session, subjects were randomly rematched into groups of five every round, therefore, a matching group of 10 subjects coincides with the session size. Common values and corresponding signals were drawn before sessions started. Draws are *i.i.d.* across rounds for common values, and error draws are also *i.i.d.* across subjects. For the experiment, we use identical draws in the identical order across treatments. Thus, treatment differences are not driven by differences in random draws. In the experiment, we truncate common value and signal draws between 0 and 200 and also only allow for bids between 0 and 200.[17]

We communicated the distributions of values and signals with the help of density plots and we allowed subjects to generate example draws for the common value and corresponding signals. At the start of each round in each auction, subjects were privately informed about their signals and the auction started as soon as all bidders in a session indicated that they were ready.

The rules of the auction formats were described in Section 3. The auction procedure was visualized with a thermometer. In the AV and the JEA, the price increased from 0 by one point every 650 milliseconds. Approximately three times per second, the program checked whether any bidder dropped out. In the JEA, bidders were shown the prices at which the first, second, and third dropout occurred. After a dropout in this auction, there was a pause of four seconds where the price did not rise to allow the remaining bidders to process the information.

[16]In the experiment, only one subject had a negative payment balance if calculating total earnings across *all* rounds. In the preregistration, we announced that we also analyze our data without bankrupted subjects. However, excluding this one subject does not affect results.

[17]We discarded a set of draws whenever a common value or signal exceeded our bounds. This occurred for 0 out 600 common value draws, and 121 out of 6000 drawn signals. Due to the small scale of this phenomenon, we ignore truncation in our analysis.

In all three treatments, at the end of each round all subjects were shown the price which the winner paid and the common value that was drawn. In each round, each bidder was endowed with 20 points, and the winning bidder was additionally paid the difference between the common value and the second highest bid. When negative, the difference was deducted.

In the 13 sessions ran in October 2018, we included two additional incentivized tasks at the end to investigate some conjectures developed after the first sessions. First, we used a measure adapted from Goeree and Yariv (2015) to elicit a subject's tendency to conform to others' choices in an environment where these choices contain no information. Subjects had an incentive to guess an unknown binary state. Their choice was to either receive a noisy but informative signal of the state, or to sample the uninformative decisions from three previous subjects. Crucially, these previous subjects had no access to any information about the true state, and subjects were made aware of this fact. Second, we obtained a measure of subjects' social preferences by using the circle test to measure their value orientation (Sonnemans, van Dijk, and van Winden (2006)). We included these measures to test some conjectures about the exit decisions of subjects with low signals in the Japanese–English auction. In addition, in the oral outcry auction we included two unincentivized questionnaire measures of subjects' tendency to succumb to endowment effects to further investigate the role of the quasi-endowment effect in this auction.[18]

Many features of our experimental design are motivated by the theoretical model with affiliated signals (Milgrom and Weber (1982)). The situation that we study is stylized, and our setup may offer more opportunities for learning than bidders would have outside of the laboratory when they bid on real commodities. In auctions outside of the laboratory, it may be much less clear to the winner that he suffered a loss, which may impede learning. In addition, our conjecture is that bidders may suffer more from endowment effects when they are bidding on a real commodity than when they are bidding on a fictitious good with induced value. From this perspective, we expect that biases may be larger outside of the laboratory.

6. Experimental results

In this section, we present the experimental results. We first present an overview of the revenues generated in the three auctions. Next, we discuss information usage in the Japanese–English auction (JEA). Then we compare the level of information aggregation in all three formats. Finally, we present evidence on jump bidding and the quasi-endowment effect in the Oral Outcry auction (OO).

In our analysis, we use data from all 30 rounds. We present results on experienced bidders in the Appendix Section A.7. Results are mostly in line with the main analysis, otherwise we address this within the main text.

[18]Question 1 was: "Suppose you paid € 30 for 5 cello lessons. After the first lesson you realize that you really don't like it. How many of the remaining lessons do you attend? You cannot get the money back." Question 2 was: "Suppose that tickets are on sale for the National Lottery to be played out in one week, with a prize of € 100.000 and you just bought one ticket for € 2.50. A colleague offers you money to buy the ticket from you. What is the minimum price at which you are willing to sell the ticket to him?"

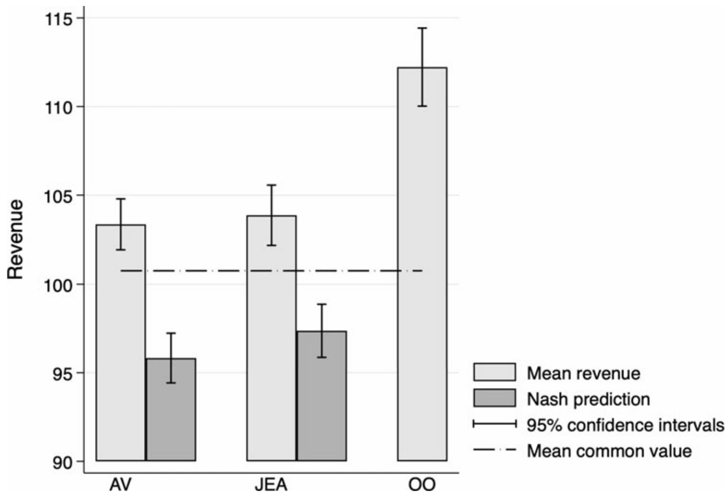

FIGURE 2. Mean revenue, Nash equilibrium predictions, and common values.

6.1 *Revenue*

Figure 2 and Table 2 present mean revenues by treatment.[19] Average revenues are quite similar in the AV and the JEA, but are substantially larger in the OO. Differences are most pronounced in the first 15 rounds, but differences continue to be significant also for experienced bidders in the last 15 rounds. Table 2 also reports test results of comparisons of revenue across treatments together with test results of the comparisons of revenues with the Nash benchmark.[20]

We find strongly significant revenue differences between the OO and both other auction formats. While the theory predicts higher revenue in the JEA than in the AV, we cannot reject equality of revenues between the two formats. In both the AV and the JEA, actual revenues deviate systematically from the Nash benchmark.

One explanation for the failure of rejecting equality of revenues between the AV and the JEA is that bidders simply ignore the information that is revealed in the JEA. Another possibility is that the more transparent JEA activates different behavioral forces that offset each other. In the next section, we explore these possible explanations.[21]

[19] In one auction in the AV, the auction unintentionally ended after only three, not four, bidders dropped out. We remove the data from this particular auction.

[20] Treatment results are robust to using parametric tests and the nonsignificance of a treatment difference is not arising from comparing matching group averages. When regressing revenues on treatment dummies, clustering standard errors on a matching group-level (600 observations per treatment), we find that compared to a baseline of the AV, the dummy on the JEA is not significant with a p-value $= 0.778$, whereas the dummy on the OO is significant at a p-value $= 0.005$.

[21] In the preregistration plan, we announced that we would compare how well rational and behavioral models organize actual bidding. It turns out that none of the models comes even close to explaining the early dropouts in the auction. As a result, we have chosen to relegate this analysis to the Appendix Section A.5.

Table 2. Revenue statistics by treatment.

Round		Revenue: Mean (Standard Deviation) 1–30	1–15	16–30
AV		103.4 (17.9)	106.1 (19.5)	100.6 (15.7)
JEA		103.9 (21.2)	106.5 (20.9)	101.3 (21.3)
OO		112.2 (27.5)	118.0 (31.2)	106.5 (21.7)
Round		**Treatment Effects: p-Values 1–30**	**1–15**	**16–30**
AV vs.	JEA	0.597	0.940	0.734
	OO	0.003	0.011	0.049
JEA vs.	OO	0.009	0.003	0.059
Round		**Revenue Difference to Nash eq'm: p-Values 1–30**	**1–15**	**16–30**
AV vs.	Nash eq'm	0.001	0.002	0.010
JEA vs.	Nash eq'm	0.001	0.000	0.049

Note: Mean and standard deviation of revenues by treatment, over time. Test results (p-values) of revenue comparisons across treatments and to the Nash equilibrium prediction. For each test, we use the averages per matching group as independent observations for the Mann–Whitney U-tests. This gives 10 observations per treatment.

6.2 *Information processing in JEA*

We find that bidders overbid both in the JEA and in the AV compared to the rational benchmark. Our data also do not agree with the revenue prediction of (Bayesian) signal averaging, according to which revenue in the JEA must be lower compared to the AV. These findings raise the question whether subjects make use in any way of the information released in the auction. One possibility is that bidders in the JEA disregard the bidding of others and only use their private information. In this section, we show that this is not the case. We start by comparing how bids correlate in the JEA with previous dropouts, and contrast this to information use in the theoretical benchmarks. Then we proceed by showing that bidders' dropouts correlate more with previous dropouts in the JEA than in the AV, in which endogenous information of others' bids is not available.

Table 3 presents the results of a fixed-effects regression analysis that models how bids correlate with available information. Define as $b_{j;i,t}$ the dropout price of bidder i in round t, where, for ease of exposition, j denotes the dropout order corresponding to that observation. Further denote with $\mathbf{b}_{j-1,t}$ the vector collecting the $j-1$ dropout prices preceding the jth bid in round t. For each $j \in \{1, \dots, 4\}$ we pool data for each dropout order j and separately estimate the models:

$$b_{j;i,t} = \alpha + \beta x_{i,t} + \boldsymbol{\gamma}^{\mathsf{T}} \mathbf{b}_{j-1;t} + \delta t + \eta_i + \epsilon_{i,t},$$

where $x_{i,t}$ is the private signal of bidder i and t is the auction round. η_i is a bidder-specific fixed effect and $\epsilon_{i,t}$ is a bidder-round error. We use the within-estimator, where

Table 3. Bidders' use of information in the JEA.

	(1) b_1 Observed	(2) b_2 Observed	(3) b_3 Observed	(4) b_4 Observed	(5) b_4 Nash	(6) b_4 SA	(7) b_4 BSA	(8) V	(9) $\widehat{BR}$
x	0.294	0.267	0.172	0.118	0.287	0.250	0.168	0.250	0.288
	(0.057)	(0.034)	(0.027)	(0.016)	(·)	(·)	(·)	(0.020)	(0.001)
b_1		0.372	0.023	0.025	0.100	0	0	−0.009	0.032
		(0.035)	(0.018)	(0.015)	(·)	(·)	(·)	(0.025)	(0.003)
b_2			0.552	−0.038	0.167	0	0	−0.003	0.060
			(0.044)	(0.037)	(·)	(·)	(·)	(0.052)	(0.003)
b_3				0.709	0.333	0.750	0.832	0.291	0.151
				(0.072)	(·)	(·)	(·)	(0.070)	(0.003)
t	−0.316	−0.122	−0.083	−0.075				0.295	0.087
	(0.281)	(0.114)	(0.074)	(0.031)				(0.073)	(0.002)
Constant	35.185	41.823	32.049	26.290	11.265	0	0	41.882	44.804
	(8.628)	(2.723)	(2.933)	(3.619)	(·)	(·)	(·)	(3.799)	(0.361)
Observations	600	600	600	600				600	600
Adj. R^2	0.119	0.491	0.756	0.817				0.362	0.996
Adj. R^2 absorb. i	0.425	0.592	0.768	0.821					
Rounds	1–30	1–30	1–30	1–30				1–30	1–30
Estimation	FE	FE	FE	FE				OLS	OLS

Note: b_j: dropout price at order j; V: common value; x: own signal. (1) to (4) are fixed effects estimates (within estimation) of information use. Dependent variables (in columns) are dropout prices at each order, for example, (1) are all bidders dropping out first in an auction. Regressors (in rows) are the available information at each dropout order, that is, the signal x and the preceding dropout prices $\mathbf{b}_{j-1}$. (5) to (7) show how information is used in three canonical models, only for the fourth dropout. SA refers to the signal averaging-rule, BSA to the Bayesian signal averaging-rule. Note that these show how theoretical bids respond to earlier bids, where these bids are also calculated to follow the theoretical models. (8) shows how the price-setting bidder would have to use information to predict the common value after observing three dropouts. (9) shows how the bidder dropping out fourth would weigh information in an empirical best response. We provide adjusted R^2 of the original within-estimated model, as well as from estimating standard OLS where we include subject-specific absorbing indicators. The latter also includes fit obtained from subject fixed effects. Standard errors in parentheses, clustered at the matching group level.

we are demeaning the variables with their time-averaged counterparts. This allows us to interpret the constant as the average intercept across bidders, and each bidder's fixed effect as the deviation in this bidder's bidding level from the average.

Models (1) to (4) provide fixed effects estimates of dropout prices regressed on available information, similar to the analysis by Levin, Kagel, and Richard (1996). There is a recurring pattern in how subjects' bids correlate with available information: Bidders' dropouts depend significantly only on their own signal and the just preceding dropout.[22] The most recent dropout receives much more relative weight than bidders' signals. Thus, bids appear to react quite strongly to the auction proceedings.[23]

[22] Conditional on using information summarized in the previous dropouts, earlier bids do not add additional explanatory power. There is indeed a correlation to earlier bids, which is fully captured in the reaction to the current dropout. Repeating (3) and (4) without b_{j-1} yields significant coefficients on b_{j-2}.

[23] This analysis does not shed light on the possibility that the strong weight on the most recent dropout is due to correlation neglect (Enke and Zimmermann (2019)). With correlation neglect, information in early dropouts is double-counted in later dropouts. In the Appendix Section A.9, we present regressions similar to the above, while excluding bidders' private information. We then predict residuals in this estimations, which capture bidders' private information (their signals and noise). We then regress later bids on all resid-

All theoretical models considered in this paper process information linearly (derivations available on request).[24] In models (5) to (7), we provide theoretical benchmarks for the fourth dropouts, representing informational weights implied by these models. These models show how bids would react to (theoretical) earlier dropouts, and are purely theoretical, not estimated.[25] By comparing estimated information use to the use implied by these models we can evaluate whether bidding strategies are consistent with any of the models, which can be helpful to predict outcomes in other auction environments.

In model (5), Nash equilibrium, bidders do not ignore information from the first and second dropouts when they choose the fourth dropout conditional on the third dropout, contrary to information usage in our data. Instead, the observed pattern is more in agreement with the signal averaging rules (models (6) due to Levin, Kagel, and Richard (1996) and (7)). Both signal averaging rules correctly predict that the last dropout is a sufficient statistic for all previously revealed information, as this bid summarizes all previously revealed information. Qualitatively, the Bayesian signal averaging rule (model (7)) performs particularly well, as it approximates the relative weight on last dropout compared to the own signal more closely than in (6). A further pattern in favor of Bayesian signal averaging is that bidders do not ignore the prior. In the AV, which offers the cleanest view on whether subjects use the prior, bids are anchored toward the mean common value. Bidders who receive a signal above 100 bid on average 72.4% of their signal, while bidders with a signal of at most 100 bid on average 117.4% of their signal.

Still, the bids predicted by the Bayesian signal averaging rule do differ significantly from observed behavior. The intercepts across all dropout orders are quite large and lead to the observed overbidding.[26] As later bids are incorporating revealed information, constant overbidding early on carries over to later bids, which then determine revenue.

One remaining question is whether observed early dropouts are informative for subsequent bidders, and in how far bidders could use these bids to improve their estimates of the common value. In Nash equilibrium, all available information should be used when best responding; see model (5). However, early bids differ systematically from Nash equilibrium bids, and are potentially less informative of the common value than they are in the Nash equilibrium. The informativeness of early bids should determine how later bids should respond to early bids. We proceed by using two types of analyses: studying (i) how informative bids are of the value and (ii) how information is used in an empirical best reply.

In estimation (8), we provide an analysis of the informational content of observed bids. We regress the common value on the information available to the bidder dropping out fourth. This analysis studies how the information available to the bidder determining the price is predictive of the common value, which at the end of each round is re-

uals. We find little evidence for strong correlation neglect, as especially residuals from late dropout orders most strongly explain variation in bids. This suggests that subjects understand that the most recent dropout contains information of the signals conveyed in the earlier dropouts.

[24] We verified that our findings are not driven by the linear impact of information, by repeating (4) and (8) with the additional regressors x^2 and $(b_3)^2$. Both are not significant in either model.

[25] Applying OLS to simulated bids also recovers the coefficients presented in Table 3.

[26] In fact, we can reject the coefficient restrictions implied by (5) to (7) in F-tests based on the estimated equation (4), with p-values $= 0.000$.

vealed to the subjects. Thus, model (8) provides a benchmark of what information is useful to bidders when attempting to predict the value using a linear rule.[27] In model (8), we observe that it is sufficient for bidders to attach positive weights only to the third dropout and own signal to predict the common value. This implies that early bids are not useful to predict the common value, which in fact our subjects appear to incorporate by disregarding this information. However, the relative weights attached to the third dropout relative to the own signal differ strongly from the rule predicting the value, as bidders appear to react too much to the third dropout given the informational content of these bids.

In (9), we study how information would be weighted in an empirical best response. In this, we assume that the two bidders that remain in the auction longest bid the expected value of the item for sale, conditional on the other remaining bidder holding an equally high signal as the own signal, and incorporating information revealed in the previous dropouts. To infer signals from early dropouts, we use linear regressions in which we regress signals on observed bids, round, session fixed effects, and signals predicted from earlier bids if available.[28] The empirical best response then equals the conditional expected value calculated on the basis of the inferred signals, under the assumptions that the other remaining bidder has a signal that equals the own signal, using the result by DeGroot (2005).[29] By assuming that the other remaining bidder has a signal that equals the own signal, the bidder beats types that are below the own type, and by doing so wins in cases where the expected profit is positive, and loses against types that are above the own type, and thereby avoids winning in cases where the expected profit is negative. Notice that the procedure is quite similar to how bidders bid in the symmetric Nash equilibrium. The difference lies in how signal are inferred from earlier bids. In the Nash equilibrium, bidders infer the signals of bidders that previously dropped out from their actual (Nash equilibrium) bidding strategies. In our empirical best response, signals are estimated from previous dropouts. We then regress the obtained empirical best response on the same set of observables for the second-highest bidder.

Consistent with the findings of model (8), (9) shows that early bids optimally receive little weight in an empirical best response. Due to early bidding being less informative than in Nash equilibrium, the optimal weights are below the weights on observed bids in model (5). However, even if the estimated coefficients are small, they are significant

[27] Note that the positive coefficient on t is a mechanical effect of all bids decreasing in t (see (1) to (4)), as V is in expectation constant over time. From experience, bidders learn that the amount of overbidding by others decreases over time (at the end of each round the common value of a round is communicated). To accommodate for this downward trend in the bidding, given the same previous dropouts, a bidder who estimates the common value will form a higher prediction of the common value in later rounds compared to early rounds. Such a compensating factor would have been absent if there had not been a trend in subjects' bidding. Allowing for a more flexible time trend in (8) with squared round or round fixed effects does not affect estimates on information use (b_1, b_2, b_3, x).

[28] We reproduce these estimations in the Appendix, Table 15.

[29] In calculating the conditional expected value, we invoke the assumption that signals inferred from previous dropouts are distributed as the true signals are (i.e., conditional on the value they are $i.i.d.$, $\mathcal{N}(0, 35)$).

Table 4. Comparing information use in the AV and the JEA.

	b_2	b_3	b_4
b_{j-1}	0.285	0.357	0.465
	(0.0309)	(0.0319)	(0.0440)
JEA × b_{j-1}	0.0871	0.195	0.244
	(0.0463)	(0.0533)	(0.0827)
Observations	1199	1199	1199
Adjusted R^2	0.502	0.732	0.777

Note: b_{j-1} denotes the just preceding dropout, for example, it is b_1 for b_2. JEA is a dummy equal one for JEA auctions. Additional variables omitted from the table: all regressions include signal x, round t, all preceding dropouts (b_{j-k} for all $k \in \{1, \dots, j-1\}$) as well as all these variables interacted with the JEA-dummy and a constant. For the full regression results, see Table 16 in the Appendix. Standard errors in parentheses and clustered at the matching group level.

and positive. Again similar to (8), (9) shows that bidders do not rely sufficiently strongly on their own signal when bidding, and disregard valuable information in bidding.[30]

Importantly, this analysis in itself does not provide evidence that bidders actively incorporate information. This is the case as the regressions in Table 3 organize bids into order statistics and this mechanically produces some degree of correlation, even if bidders were to ignore entirely the bidding behavior of others. Given that a bidder's bid is noisy and not completely determined by the own signal, information will be conveyed in the previous dropout(s). As an illustration, consider the case in which the previous dropout is very high, in fact, higher than the expected current dropout conditional on own signal. Then, by definition, the expected current dropout conditional on previous dropout and own signal will be higher than the expected dropout level conditional on own signal only, thus leading to positive residual correlation between dropout orders.

This produces a mechanical correlation between dropouts and previous dropouts even if bidders do not pay any attention to the previous dropouts.

In order to use correlations among dropout prices as evidence for information processing, we need to move from an absolute to a comparative approach. In Table 4, we show excerpts from regressions where we pool data from the AV and the JEA and regress bids on the previous dropouts, signals, and interactions for the JEA. We refer to Table 16 in the Appendix for the full results. In the AV, where by design no information can be extracted from the unobservable bidding of others, we observe the mechanical correlation in dropout order statistics, as all coefficients on the just preceding dropouts $b_{j-1,t}$ are significant at conventional levels. Using the bidding in the AV as a benchmark, we measure the amount of information processing in the JEA by computing the additional correlation observed in the JEA compared to the AV. Table 4 shows that the slope parameters on every just-preceding bid are statistically larger in the JEA compared to the AV at each dropout order. As bids in the JEA are more strongly correlated than in the AV, we can conclude that bidders do react to the information contained in the bids of others.

To sum up, we conclude that subjects' bidding is consistent with them paying attention and responding to the bids of others in the JEA. Compared to the empirical best

[30]Note that R^2 is mechanically high in this regression because the best response is calculated as a linear function of the bids.

response, subjects pay too much attention to the most recent dropout and underweigh their own signal. How subjects' bidding weighs information in the own signal relative to the observed dropout is qualitatively in line with Bayesian signal averaging. Still, our data does not accord with the prediction of the Bayesian signal averaging model that lower revenue will result in the JEA than in the AV. In the next section, we address how heterogeneity in early bidding contributes to understanding this puzzle.

6.3 *Exploring heterogeneity in bidding*

In this section, we investigate whether individual-specific characteristics correlate with bidders' behavior in early dropouts. Bidding behavior in the JEA is quite heterogeneous, and especially so at early dropouts, in Table 3, we see that the R^2 increases in dropout orders. Additionally, especially at early dropout orders, subject-level fixed effects bring in significant additional explanatory power. Our finding that individual-specific characteristics matter more at early stages of bidding in the JEA agrees with the observation that deviations from the theoretical benchmark are less costly at these early stages in this auction format. For instance, a bidder who considers dropping out first may choose to overbid almost without costs: even when overbidding, the bidder can avoid winning by immediately dropping out when others do so. Likewise, if this bidder decides to drop somewhat earlier than the theoretical benchmark, this also happens almost without costs because the chances that all the others would drop before the theoretical benchmark is negligible if no other bidder has dropped out yet.

To shed light on whether there are systematic patterns in this heterogeneity in bidding behavior, we elicited subjects' social value orientation and their tendency for imitation at the end of the experiment for the last 13 sessions.[31] For the imitation measurement, subject could choose to sample noninformative social information of prior participants instead of obtaining an informative signal. This behavior is consistent with a desire to imitate others. Participants that chose to reveal uninformative choices are classified as imitators, which applies to 26.9% of our participants.[32] Social value orientation is measured as an angle, where 0° correspond to a dictator keeping all to herself, 45° giving an equal amount to recipient and herself, and 90° giving everything to the recipient. We find an average SVO of 21.13°, with a standard deviation of 19.93°.

To investigate whether these measures correlate with heterogeneity in bidding behavior, we exploit that the estimations in Table 3 provide us with estimates of bidder fixed effects. In this context, the bidder fixed effect captures bidder-specific level shifts

[31] Another candidate to explain deviations from risk neutral Nash bidding is risk aversion. Because all auctions use the second-price rule and there is uncertainty about the value, risk aversion will have a downward pressure on Nash equilibrium bids (see also Levin, Kagel, and Richard (1996)). Given that observed bids tend to be higher than risk neutral Nash equilibrium bids, we think that risk aversion is a less important force in our experiment. Similarly, the heterogeneous behavior of early dropouts is not only incompatible with the symmetric equilibrium in Milgrom and Weber (1982), but also with the asymmetric equilibria in open auctions identified by Bikhchandani and Riley (1991). In addition, the asymmetric equilibria predict lower revenues in the JEA, while we observe revenue in excess of the symmetric Nash equilibrium.

[32] In a similar setting, Goeree and Yariv (2015) find that 34% of subjects chose such information.

Table 5. Bidder fixed effects and their characteristics.

	(1)	(2)	(3)	(4)
	Average Bidder Fixed Effect			
	b_1 & b_2		b_3 & b_4	
	AV	JEA	AV	JEA
SVO	0.125	−0.202	0.005	0.027
	(0.045)	(0.146)	(0.120)	(0.078)
Imitator	5.699	5.213	6.528	1.575
	(1.479)	(3.823)	(3.121)	(0.471)
Constant	−1.876	6.225	−4.674	−1.080
	(1.919)	(2.363)	(1.678)	(2.681)
Observations	50	40	50	40
Adjusted R^2	0.031	0.014	0.048	−0.031

Note: Average fixed effects from regressing bids on available information for first and second versus third and fourth dropout. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. Standard errors in parentheses, clustered at the matching group level.

of bids, holding the use of information constant across bidders. Crucially, identical bidders may behave differently between different auction formats, especially as behavioral motives may be differentially triggered. Note that our within-estimations impose that the average bidder fixed effects have a mean of zero. This means that any bidder's fixed effect can be interpreted as a deviation from the average bidding behavior within our sample for each treatment.

Per participant, we average the fixed effects of the first and second dropouts as well as the fixed effects from the third and fourth dropout. For the AV and the JEA separately, we then regress the averaged fixed effects on subjects' social value orientation and imitation proneness. Table 5 presents OLS estimates.[33]

In both treatments, estimates imply that imitators are willing to bid higher than non-imitators. The effects ares similar in size but only significant in the AV, which may be due to a lack of power. In any case, the fact that the bids of imitators are not higher in the JEA than in the AV hints at the possibility that this measure may not only capture a tendency to imitate but also general overbidding caused by confusion.[34] From this perspective, imitation is not a good candidate to explain differential bidding in the early dropouts between the two auction formats.

[33] Note that the fixed effects are estimated, and thus may contain noise from the first stage in this estimation procedure. In the Appendix, Section A.10, we show that point estimates are similar using WLS, which addresses concerns that some fixed effects might be estimated more noisily than others. These observations receive less weight in variance-weighted WLS. The estimates on SVO and Imitator in (2) are significant in this specification, which suggests that the noise in estimating fixed effects may be important. Point estimates with experienced bidders are mostly similar; see Table 13 in the Appendix. The coefficient on Imitator is insignificant across specifications (1) to (3), and the coefficient on SVO is significant and positive in (3) and (4).

[34] There are also situational factors that affect the extent of overbidding. For instance, Levin, Kagel, and Richard (1996) and Goeree and Offerman (2002) find that subjects' overbidding enhances with the variance of the noise term in the signals.

Our conjecture was that SVO would explain differences in the early bidding between the two auctions. The coefficient for SVO in column (2) of Table 5 is in line with the conjecture that spiteful bidders bid higher early in the JEA to drive up the price for others: only in JEA the coefficient is negative. However, the standard error is large, and we cannot conclude whether there is a negative effect or no effect of SVO on early bidding in JEA.[35]

Given that the evidence in Table 5 is not conclusive about the effect of SVO on early bidding in JEA, we looked further into how SVO affects bidding in the two auction formats. As we expected when we decided to measure SVO, competitors, those with below-median SVO, bid on average 71.3 in the first two dropouts in JEA, significantly more than in the AV where they bid on average 56.4 in the first two dropouts (Mann–Whitney U-test, 9 observations, p-value $= 0.086$). This finding reflects that driving up the price for others is relatively cheap in the JEA, because this format allows bidders to enhance the price for others without much risk of actually winning the good. To put things into perspective, it is not clear that cooperators bid significantly more in the early dropouts of the JEA than in the AV (average bid of 59.6 in the AV versus 70.8 in the JEA; Mann–Whitney U-test, 9 observations, p-value $= 0.327$).

Figure 3 displays for each of the two auction formats the SVO per dropout order. Whereas there is a slight increase of SVO over dropout orders in the AV, there is a surprising but intuitive pattern in the JEA: Bidders who drop out first or last have on average a higher SVO than bidders who drop out in the middle. This suggests that cooperators decide at the start to either be nice and drop out first or to go all-in in a serious attempt to win the auction. By doing so, they would refrain from driving up the price for others when they do not win. In the cases where they decide to win the auction, cooperators have to outbid spiteful bidders, who are bidding more aggressively than they would have in the AV. We find that cooperators (with an SVO above the median) end up significantly more often in an extreme position (either first or last) than competitive bidders (those with an SVO below the median): Mann–Whitney U-test, 8 observations, p-value $= 0.043$. This pattern only materializes in the JEA: the same test for the AV is insignificant (p-value $= 0.917$, 10 observations).[36]

Overall, our suggestive evidence is consistent with the following picture of how SVO may affect bidding in the two auction formats. In the JEA, spiteful bidders tend to bid higher at the start than they would have in the AV, because the information about how many other bidders are still active makes it cheap for them to overbid. Without too much risk, they can stay longer in the auction and drive up the price without actually winning

[35] Somewhat surprisingly, more pro-social bidders bid slightly higher on average in the early bidding in the AV. Note that for the SVO, inequality averse participants are classified as pro-social. Therefore, bidding higher initially in the AV can be consistent with bidders trying to minimize payoff inequality, which might arise if an opponent wins at a low price. Pro-social bidders' behavior is not significantly different in the early bidding across auctions.

[36] To verify that the difference between treatments is significant, we run a logistic regression. We regress the binary dependent variable (0 if dropping out first or last, 1 otherwise) on SVO, Imitator and signal, a treatment dummy as well as interactions of all independent variables and treatment. While the coefficient on SVO is not significant (p-value $= 0.817$), the coefficient on the interaction of JEA and SVO is negative and (weakly) significant (p-value $= 0.071$).

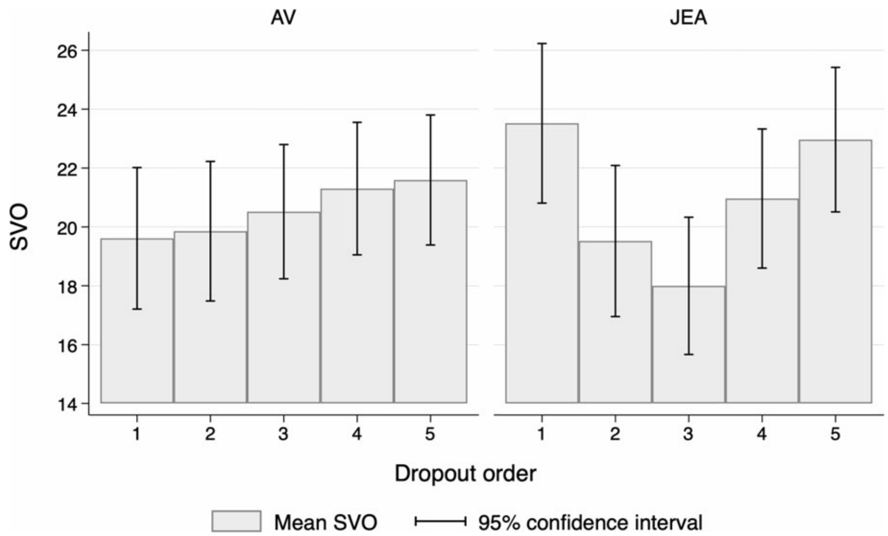

Figure 3. SVO by dropout order.

the object. Cooperators on the other hand decide at the start of the auction whether or not they want to compete and win the object for sale. If their signal makes them decide it is better not to win, they drop out early and by doing so refrain from enhancing the price for others. If they decide to compete, they relatively often end up winning the auction. In this case, they have to outbid spiteful bidders who tend to bid higher than they would have in the AV.

6.4 *Information aggregation*

Previously, we showed that bidders engage in overbidding (Figure 2). Even bidders who depart from rationality can convey information in their bids, or infer information from others' bids. For instance, if bidders follow a behavioral model, then their bids will still convey information about their signals. If this is anticipated by other bidders, bidders can still process this information in their own bids. In this section, we investigate the extent to which bidders aggregate information in the different auction formats. The measure of information aggregation is the squared distance between the price and the common value, as discussed in Section 4.

We first present a comparison between the JEA and the AV, the two auctions that differ only in the information on previous dropouts. Both rational and behavioral benchmarks predict that additional information improves bidders' precision in estimating the value. This prediction, however, is not borne out in our data. Figure 4 plots the distance between price and value that is actually observed in the data. For a comparison, it also includes Nash equilibrium predictions.

As it turns out, the theoretically predicted ranking is reversed in our data. The observed squared distance in the AV is 411.9, and *increases* to 479.1 when *more* information is available in the JEA. This difference is statistically significant (Mann–Whitney U-test,

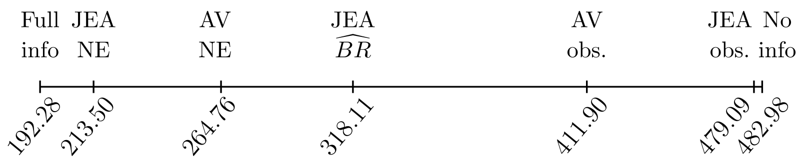

Figure 4. Squared distance to common value.

10 observations per treatment, p-value $= 0.028$). Actually, the JEA aggregates almost no information. The observed squared distance of the JEA is not statistically different from the No Information benchmark, where the price is set equal to the prior mean of the common value, ignoring all information contained in signals.[37]

There can be two reasons why information aggregation fails in open ascending auctions: (i) there is not sufficient informational content in observable bids (*information revelation*) (ii) bidders do not process the available information as a rational bidder would (*information processing*). To isolate the two forces, we use an empirical best response $\widehat{BR}$ as described in Section 6.2, given observed bidding behavior of early dropouts.

Note that $\widehat{BR}$ is a statistic that separates between information processing and revelation. It represents the level at which the two remaining bidders best respond to each other, when they incorporate information available in the experiment. The gap between the observed level of information aggregation (JEA obs.) and the maximal level of aggregation achievable given the available information ($\widehat{BR}$) serves as our measure of the failure of information processing. Failure in information revelation is measured by the distance between $\widehat{BR}$ and JEA NE, as in Nash equilibrium signals from earlier dropouts can be inferred perfectly. From inspecting the segment, it is apparent that both forces play a role: Information in the JEA is dissipated by noisy early dropouts and further processed in a sub-optimal way.

Using the empirical best response, we can also provide a lower bound for the importance of heterogeneity in early dropouts on the failure of information aggregation. Using bidder fixed effects, instead of only session fixed effects, when estimating signals from observed bids, the squared distance of the empirical best response to the common value reduces to 303.0. The difference of this new benchmark to the empirical best response is significant (Wilcoxon signed-rank test, 10 observations, p-value $= 0.047$). Note that this is a lower bound due to the role played by individual heterogeneity, as it ignores the additional gains brought about by bidders iteratively making the intermediate dropouts more precise, something they cannot do as the identity of other bidders is not observed.

Lastly, when it comes to our third auction format, the OO, the higher revenue that we observe is not caused by a higher degree of information aggregation in this format. To the contrary, in the OO overbidding is so severe that the price is a highly inaccurate

[37]We verified that the same ordering in our results on information aggregation is observed when using the squared distance to the Full information benchmark as a measure, instead of the squared distance to the common value. The latter does not directly control for variance in signals conditional on the common value. In our analysis, this is captured by the distance to the common value measured in the Full information benchmark.

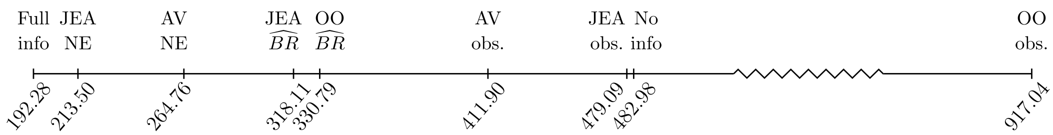

FIGURE 5. Squared distance to common value, including the OO.

predictor of the common value, resulting in a very imprecise measure of information aggregation, with a squared distance of 917.0. If bidders had simply ignored their private signal and the bidding of others, and bid the prior mean value according to the no-information benchmark, this distance would shrink to 483.0. Figure 5 presents the information aggregation benchmarks of the OO in comparison to the other auction formats.

This lack of information aggregation cannot be attributed to information in bids being obfuscated. The same decomposition as performed for the JEA shows that the second-highest bidder in the OO would be able to predict the common value relatively well if they attempted to bid the conditional expected value as in the JEA, by incorporating the own signal and the maximal bids of the three non-winners. This is a conservative measure of how much information is potentially available in the OO, because it ignores other, possibly informative, observables such as the time elapsed between bids, the size of the jump bids, or the number of returning bidders.

6.5 *Bidding in Oral Outcry auctions*

We have previously seen that revenue is higher in the OO than in the other two formats. Also, information aggregation in this format fails.

The OO differs from the two clock-formats in how bids can be submitted. In both the AV and the JEA, the price rises at an exogenously set pace and bidders can only decide whether to leave or remain at every price. In the OO, bidders can submit their own bids. In the following, we discuss two ways in which this change matters: it may trigger a quasi-endowment effect in bidders, as well as allow for non-incremental jump bidding.

During an Oral Outcry auction, a standing bidder is identified, who is the highest bidder at that moment. The previous literature has established that this can induce a so-called auction fever (Heyman, Orhun, and Ariely (2004), Ehrhart, Ott, and Abele (2015)). A standing bidder may get used to the feeling of winning the good and become prepared to bid higher than she originally intended. If that happens, auction fever triggers a quasi-endowment effect.

Auction fever is in agreement with the fact that, beyond the average revenue already being significantly higher, we also observe relatively many extreme auction revenues in the OO compared to the other two formats. For example, only 1.3% of all common values are in the right-hand tail of the common value distribution, at values above 150. In both the AV and the JEA, less than 1% of auctions end up at revenues above 150. In the OO in turn, 7.3% of auctions conclude at prices above 150, suggesting that especially this format triggers strong mispricing.

To evaluate the impact of auction fever, we use bidder's exogenously measured inclination to succumb to the endowment effect, and perform a median split based on this measure.[38] There are two main effects: (i) bidders do not systematically differ in how often they win auctions (Mann–Whitney U-test, p-value $= 0.773$), thus bidding behavior appears similar at first; (ii) whenever they win an auction, bidders with stronger endowment effects generate higher losses than their peers, as their total profits are significantly different (Mann–Whitney U-test, p-value $= 0.083$),[39] thus when becoming active and winning an auction, bidders with strong endowment effects lose more money. This evidence provides support for the conjecture that the OO activates auction fever among people who suffer from the endowment effect.

A second important feature of the OO is that bidders can submit nonincremental jump bids. Theoretical analyses of jump bidding suggest that this may be a profitable strategy for a jump-bidder. Avery (1998) derives equilibria in which jump bidding is used for signaling high value estimates, which predicts increased profits for the winner. Ettinger and Michelucci (2016) show that jump bidding can be used to obfuscate information. Naturally, behavioral factors may also affect jump bidding. For example, impatient bidders who are determined to win an auction quickly might frequently submit jump bids, which lead them to win auctions in cases in which they have initially overestimated the value, an error which could have been corrected in the price discovery of an incremental bidding process. These behavioral factors suggest that jump bidding may also be costly and reduce winners' profits. In the following, we evaluate the effect of jump bidding in the OO auctions, focusing on whether jump bidding increases profits.

Note that within our auctions and due to the second-price rule in setting the current price, jump bids are only revealed if at least one other bidder continues to bid. While submitting additional bids, other bidders learn that the jump bidder has entered an aggressive jump bid, as the jump bidder continues to be the standing bidder. The level of the jump bid is revealed at the moment that some other bidder enters a bid higher than the jump bid. This feature captures how jump bidding in popular auction formats occurs. As such, we expect weaker effects of jump bidding than in first-price formats, where the level of a jump bid is revealed immediately. In our analysis, we will show that even this subtle effect of jump bidding matters for outcomes.

As a measure of jump bidding, we construct the total jump bid of each bidder in each round. To do so, we first calculate the increment of a new bid above the current price, the second highest bid submitted in previous bidding rounds, at the moment the new bid was submitted. By the rules of the auction, this increment varies between 1 point, which is the minimum increment, and 200 points, if the maximum possible bid was submitted straight at the start of the auction. Often, the same bidder submits multiple bids. We

[38] We normalize both measures to mean 0, variance 1, then take the average response as a measure of the endowment effect. We compare matching group averages of those bidders with above and below median endowment effects, yielding 8 observations (4 matching groups, one observation above and below the median each).

[39] This analysis is robust to performing a median split based on the first principal component obtained from the two measures of the endowment effect, with p-values of.564 and.083, respectively (Mann–Whitney U-tests, 8 observations).

denote the sum of all increments for one bidder across one auction as the total jump bid of this bidder.

We observe extensive jump bidding: 21.6% of bids exceed the current price by at least 20 points, and 11.2% by at least 50 points. Jump bidding is most prevalent at the start of an auction, where 81.7% of entered bids are at least 20 points, and 60.4% are at least 50 points high. Jump bidding also gains in popularity over time: in the first 15 rounds, the average jump bid at the start of an auction is 53.8, this increases to an average of 61.6 in the last 15 rounds.[40]

In Table 6, we show regression results on the use and effect of jump bids. The main regressor of interest is the total jump bid, the sum of all bid increments by each bidder in an auction. However, in regressions studying the effect of jump bids, these bids are likely endogenous as strategies adjust to observed jump bids submitted earlier. To account for this, we rely on instruments generated from other rounds, which capture an individual bidder's proneness for jump bidding. As instruments, we use the average total jump bid of each bidder across all other rounds, as well as the maximum bid increment in any of the other rounds. Using 2SLS, we then predict in a first stage the total jump bid in the current round using the two instruments and other variables, such as the signal x. In the second stage, we regress our dependent variables of interest on the predicted total jump bid and some other variables. This provides a clean identification of the effect of jump bids. For relevance, we here assume that a bidder's proneness to jump bid in other rounds correlates with this bidder's jump bidding in the particular round. For the exclusion restriction, we assume that other rounds' jump bids only affect outcomes through the bidding in that particular round. We think that this is plausible for two reasons. First, the only way of affecting a particular round's outcomes is only through bidding in that round, while other rounds' bids (our instruments) cannot directly affect outcomes by the auction rules. Second, as for potential indirect effects, this exclusion is reinforced by our experimental design, as every round bidders draw new random signals and are allocated to new random groups within the matching group, which limits the effects other rounds' behavior may have on this round's competitors. In the Appendix Section A.11, we present first-stage regression results in combination with a robustness check based on the use of only the average total jump bids across all other rounds as instrument. We show that the instruments are relevant, as all first stage regressions are significant at conventional levels, with Kleibergen–Paap F-statistics of 96.4 or greater. In addition, we show that we cannot reject the null hypothesis that the instruments are valid, with p-values of the Hansen J-statistic of.582 or higher.

Column (1) presents results of regressing these jump bids on bidders' information. As predicted by theoretical models, bidders with higher signals submit higher jump bids.

[40] In the first six sessions, the bidding rounds at which a bid was submitted was not saved correctly due to a programming mistake. We reconstructed this data by the time stamp at which bids were submitted. In 10.7% of the bids in these sessions, this classification is potentially ambiguous, we assumed that bids were submitted in a later bidding round in these cases, which leads to potentially fewer bids being considered for our type of analysis. The results we present are robust to instead assuming that these bids were submitted simultaneously, or randomizing this classification. Also, only using data from the last four sessions, where this error was corrected, yields similar results.

Table 6. Effect of jump bids in the OO.

	(1)	(2)	(3)	(4)
	Jump Bid	Pr (Win)	Profits	Winners' Profits
Total jump bid (IV)		0.350	−0.261	−0.316
		(0.083)	(0.115)	(0.133)
x	0.276	0.144	−0.067	−0.029
	(0.031)	(0.038)	(0.037)	(0.042)
t	−0.138		0.877	0.784
	(0.124)		(0.169)	(0.154)
V			0.624	0.633
			(0.046)	(0.064)
Constant	30.433	−12.306	−66.653	−58.996
	(5.897)	(2.656)	(7.000)	(9.917)
Observations	2687	2687	2687	600
Adjusted R^2	0.070	0.102	0.291	0.287
Estimation	OLS	2SLS	2SLS	2SLS

Note: Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In (1), we regress total jump bid on bidders' signals and round t. In (2) to (4), we use 2SLS, where we instrument using the average total jump bid and the maximum bid increment in other rounds. (2) is the ex post probability of winning, which is a dummy equal to 100 if a bidder wins the auction, 0 otherwise. Mean earnings are a participants' average earning across all auctions, winners' profits are the earnings for the auctions which a participant won. x is the submitting bidder's signal in round t. V represents the common value. Standard errors in parentheses, clustered at the matching group level.

The size of the jump bid is not significantly increasing over time. Interestingly, this suggests that bidders with more experience shift their jump bids to the start of the auction, as we do observe a significant increase in jump bidding at the start over time while overall jump bidding remains constant.[41]

Table 6 also presents an analysis of the effects of jump bids. In (2), the dependent variable is a dummy equal to one when a bidder wins the auction, 0 otherwise. Here, we show that, controlling for own signal, a larger jump bid increases the likelihood to win the auction. This is consistent with the signaling motive in the theoretical literature.

Models (3) and (4) then study how profits are affected by the size of the jump bid. Contrary to theoretical predictions, profits are significantly decreasing in the size of the jump.

Winners on average lose money in the OO and, by submitting a jump bid, participants select into this group of winners making a loss. Model (4) studies whether this selection effect is the full reason beyond the negative relation between jump bidding and profits. We do so by restricting the analysis to bidders who end up winning the auction. We find that even within this group of bidders, the size of the jump bid decreases profits further.

Results for experienced bidders are similar; see Table 14 in the Appendix. In later rounds, jump bidding has a slightly less pronounced effect on earnings and profits. Still,

[41] In the last four sessions, we elicited how much participants agreed with several motives for jump bidding in the questionnaire; see Appendix Section A.12 for details. If we include those in (1) as controls, the only statement that correlates significantly with the size of the jump bid is "I tried to deter other bidders from bidding by entering a bid much higher than the current price."

jump bidding continues to be a disadvantageous strategy also with more experience, while jump bidding is in fact used more extensively later on.

7. Conclusion

In this paper, we study some salient factors that can contribute to the popularity of open ascending auctions. In particular, we assess the roles that endogenous information aggregation and behavioral biases play in explaining their prevalence. In a common value setting, we compare two clock auctions, the ascending Vickrey auction (AV) and the Japanese–English auction (JEA), which differ in irrevocable exits of bidders being observable only in the latter. We also study the Oral Outcry auction (OO), an auction format modeled to approximate popular designs, in which bidders choose how much information they want to reveal through bids.

In agreement with their popularity, we find that the OO is most successful in raising revenue. The JEA and the AV both raise higher revenue than expected in the symmetric Nash equilibrium. In contradiction to some behavioral models that predict higher revenue for the AV, we do not reject equality of revenue between the JEA and the AV. We find that information aggregation fails in the JEA. Bidding in the JEA reflects a worse estimate of the common value than in the AV.

It is not the case that bidders do not pay attention to early exits in the JEA. To the contrary, bids correlate more strongly with the most recent dropout than in the AV benchmark.[42] The bidding pattern, however, deviates from what would be observed when bidders bid according to the Nash equilibrium benchmark, and also from what would be observed when they choose empirical best responses. The relative weight of how bidders incorporate information is best captured by a Bayesian signal averaging heuristic. However, all models incorporating public information underestimate bid levels and bidders in the JEA do not use public information sufficiently to tamper the winner's curse, as predicted by signal averaging models.

At the same time, bidding behavior conveys less information than the theoretical benchmark. The information reflected in early dropouts of the JEA is partly obfuscated by heterogeneity in the bidding of early leavers. In agreement with the fact that it is relatively cheap to drive up the price in the JEA, spiteful bidders may stay longer in the JEA than in the AV, forcing cooperators to stay longer in the cases where they want to win. Such spiteful bidding by early leavers may neutralize the revenue diminishing force of the Bayesian signal averaging heuristic. Our support for a spiteful motive resonates with some empirical findings in other auction environments (Andreoni, Che, and Kim (2007), Bartling and Netzer (2016)).

In the OO, bidders choose how much information to reveal through their bids. Overall, bids in the OO convey as much information as those in the JEA. However, in the OO-format the available information is least well processed, and the price paid by the winner is the worst approximation of the common value among all three formats.

[42] Note that Hoelzl and Rustichini (2005) find that people are underconfident in complicated tasks. Their result agrees with our finding that bidders place more weight to what others do in the strategically complicated common value setup.

Instead, the OO activates some behavioral biases that enhance revenue. Bidders who suffer from endowment effects lose more money in these auctions. When they become the provisional winner, auction fever strikes and they become willing to submit higher bids than otherwise expected. In addition, the OO encourages bidders to submit jump bids. In contrast to the theoretical literature, jump bids do not enhance winners' expected profits. Jump bidders are more likely to win the auction, but they tend to lose money doing so.

OO auctions may be popular not because they allow bidders to aggregate information. Instead, a more important rationale for using OO auctions may be that they activate revenue enhancing behavioral biases.

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